

Integrated Detection and Classification of Low-Frequency Earthquakes Using a PhaseNet-Based Deep Learning Framework

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Abstract

This study develops a deep learning–based framework for detecting and classifying low-frequency earthquakes (LFEs) and ordinary earthquakes using continuous seismic waveform data. We extend the PhaseNet architecture to a five-class model that predicts probabilities for P and S phases of both ordinary earthquakes and LFEs, as well as noise. The model is trained using waveforms associated with manually determined hypocenters from the Japan Meteorological Agency (JMA) unified catalog for 2014–2022. The trained model is then applied to continuous waveform data for automatic phase picking, phase association, and event location. To evaluate the likelihood that each detected event is an LFE, we further introduce a quantitative index, called LFE-likeness (LIKE), based on the median LP and LS probability scores at the stations used for event location, where LP and LS correspond to LFE P- and S-phase probabilities, respectively. This approach enables detection and classification of seismic events within a unified framework. Application to seismic activity in northern Yamaguchi Prefecture from February to April 2025 shows that the proposed method detects more than twice as many events as the JMA catalog, including many small events not previously identified. The proposed framework provides a robust and scalable approach for integrated seismic monitoring, improving the detection of weak events and offering new insights into fluid-related seismic processes in the deep crust.

Keywords

PhaseNet, Low-frequency Earthquake, Hypocenter location, Automatic classification of earthquake types

1. Introduction

Low-frequency earthquakes (LFEs) are earthquakes whose seismic energy is dominated by lower frequencies than expected from their magnitude. In ordinary earthquakes, even events with magnitudes of about 1 often exhibit dominant frequencies of around 10 Hz or higher in velocity waveforms, whereas LFEs are dominated by waves in a clearly lower-frequency band. In addition, LFEs are characterized by less distinct P-phase onsets, relatively large S-phase amplitudes, longer shaking durations, and longer source durations than ordinary earthquakes.

LFEs are known to occur not only in the shallow crust of geothermal and volcanic regions but also at depths ranging from the lower crust to the upper mantle, where they are referred to as deep low-frequency earthquakes. Deep LFEs have been reported in both volcanic (e.g., Minakami, 1960; Ukawa and Ohtake, 1987) and non-volcanic regions (e.g., Kamaya and Katsumata, 2004), particularly near plate boundaries in subduction zones (Obara, 2002). LFEs occurring in swarms along plate boundaries are known as deep low-frequency tremors. The LFEs are thought to be closely related to fluid migration, such as magma and water migration (Chouet, 1996; Ohmi and Obara, 2002; Audet and Bürgmann, 2014), or to aseismic slip occurring on fault planes (Ide et al., 2007). Therefore, they constitute important observational targets for understanding deformation processes in the deep crust, slow earthquake activity, and the generation processes of large earthquakes (Bostock et al., 2012; Peng and Gomberg, 2010; Obara and Kato, 2016).

Because LFEs often have small amplitudes, are dominated by low-frequency components, and have unclear P-phase onsets, they are often difficult to detect using conventional detection and picking methods employed in standard seismic observations. For example, in the routine processing of seismic observation data by the Japan

Meteorological Agency (JMA), a commonly used procedure involves detecting events based on statistical change-point detection applied to continuous waveforms. This is followed by reading phase arrival times, hereafter referred to as picking, and phase association for hypocenter determination (Tamaribuchi et al., 2016; Tamaribuchi, 2018). The catalogs generated through this processing, which include many automatically determined hypocenters, provide fundamental data for continuous seismicity monitoring. However, several difficulties arise when applying such automatic processing to LFEs.

In ordinary inland earthquakes, the onset of seismic phases is relatively clear, making automatic picking comparatively straightforward, and phase association and hypocenter determination are often performed stably. In contrast, for LFEs, especially due to the unclear onset of the P phase and the frequent occurrence of many events in a short time, automatic picking and phase association become difficult. Therefore, in actual operations, operators often visually inspect waveforms to evaluate whether there are misidentifications or missed picks in the automatic processing results and perform manual repicking when necessary. Furthermore, the identification of whether an event is an LFE also depends on visual judgment based on waveform shape and frequency characteristics, and it has been pointed out that this process depends on the experience of the observer (e.g., Yoshida et al., 2020).

A widely used effective method for detecting LFEs is template matching (matched filter analysis; MFA). In this method, known LFE waveforms are used as templates, and similar events are detected by calculating cross-correlations with continuous waveforms. It has been reported for many regions that MFA can detect several times to several tens of times more LFEs compared to conventional detection methods (Shelly et al., 2007; Bostock et al., 2012; Frank et al., 2014). For example, studies applying MFA to the Nankai Trough

(Kato and Nakagawa, 2020) have detected tens of times more low-frequency earthquakes than those in the existing catalogs. Similar MFA methods have been utilized since 2018 in the JMA operational processing to detect deep low-frequency tremors along the Nankai Trough (Moriwaki, 2017).

On the other hand, automatic detection based on signal amplitude or change-point detection is performed in conventional earthquake detection processing, and therefore it is possible that a considerable number of small events and low-frequency earthquakes are overlooked at the initial processing stage. Since MFA strongly depends on known events used as templates, the number of events included in the initial catalog greatly influences the detection performance. In addition, the computational cost becomes large when a vast number of templates or long-term continuous waveforms are used. Therefore, increasing the number of events detected during the creation of the initial catalog is important not only for improving the detection capability of MFA through an increase in templates but also for performing efficient analysis (Scotto di Uccio et al., 2023; Naoi et al., 2025).

In recent years, methods using machine learning, especially deep learning, have rapidly developed in seismic waveform analysis. Deep learning models have been reported to exhibit high detection performance even for waveforms with low signal-to-noise ratios and have been applied to earthquake detection and arrival-time estimation (Ross et al., 2018; Münchmeyer et al., 2022). Furthermore, it has been reported that applying deep learning for detection and arrival-time estimation of LFEs increases the ability to identify weak events that are difficult to detect using conventional methods (Thomas et al., 2021; Münchmeyer et al., 2024; Tokuda and Nagao, 2023; Lin et al., 2023). However, many of these studies primarily focus on method development for specific regions or on evaluating detection capabilities. Relatively few studies have addressed automatic catalog generation

methods that integrate ordinary earthquakes and LFEs within the framework of routine seismic data processing.

In this study, based on the architecture of PhaseNet (Zhu and Beroza, 2019), we modified the output layer of the model to predict five probability values corresponding to the P and S phases of ordinary earthquakes, the P and S phases of LFEs, and noise. The model was first trained using waveform data compiled by Naoi et al. (2024), covering the period from 2014 to 2022. We then applied this trained model to continuous waveform data in inland areas of the Chugoku region to automatically pick phase arrival times, associate phases and determine hypocenters, thereby constructing an event catalog. Finally, we examined a method to distinguish ordinary earthquakes from LFEs by calculating an LFE-likeness index for each event, based on the probabilities that the picked phases correspond to LFEs.

When this method was applied to northern Yamaguchi Prefecture, where swarm seismic activity accompanied by LFEs occurred from February 1 to April 30, 2025, it was found that most earthquakes could be classified into ordinary earthquakes and LFEs, at a level comparable to visual inspection. In addition, numerous small earthquakes not listed in the JMA catalog were detected. The detailed seismicity and LFE-likeness index obtained by our method reveal that many LFEs that cannot be distinguished by visual inspection or conventional frequency analysis are included in the event catalog. Moreover, their spatiotemporal hypocenter distribution and velocity structure analysis is consistent with the presence of fluid flow from the upper-mantle or lower crust.

2. Development of a Deep Learning Model for Distinguishing Ordinary

Earthquakes and LFEs in Phase Picking

2.1. Model Architecture and Training Based on the JMA Unified Hypocenter Catalog

In this study, we trained a model in which the output layer of the PhaseNet model was extended from the original three categories—P-wave arrival score, S-wave arrival score, and noise—to five categories: P-wave arrival score for ordinary earthquakes (OP), S-wave arrival score for ordinary earthquakes (OS), P-wave arrival score for LFEs (LP), S-wave arrival score for LFEs (LS), and noise. This model enables phase picking for both ordinary earthquakes and LFEs. The total number of trainable parameters is 268,461. Following Zhu and Beroza (2019), training was conducted using three-component waveforms sampled at 100 Hz with 3001 samples (30.01 s). For the ground truth labels, each picked arrival time was represented by a Gaussian distribution centered on the pick, with a standard deviation of 0.1 s. Waveforms were extracted based on a window of 20 s before and 10 s after the picked arrival time reported by the JMA, with an additional random perturbation of ± 19 s applied to the window. The extracted waveform for each sample was normalized using z-score normalization. This procedure prevents the model from learning the timing of waveform extraction itself. For the test data, waveforms were extracted starting 6 s before the first labeled pick in each waveform.

For model training, we used event waveform data corresponding to picking values in the JMA unified hypocenter catalog (hereafter, JMA catalog), which were compiled by Naoi et al. (2024) for retraining PhaseNet (Zhu and Beroza, 2019) and its extension PhaseNetWC (Naoi et al., 2024). In this study, among the data obtained from 2014 to 2022, we used events whose hypocenters were determined through manual processing (hypocenter determination flags of K, k, S, or s; JMA, 2024). For ordinary earthquakes,

we used data for which both P-wave and S-wave picks were available at each station. For LFEs, we used data for which a pick was available for either the P wave or the S wave.

The obtained dataset was randomly divided into training, validation, and test datasets in a ratio of 8:1:1. The breakdown of extracted waveform data is shown in the table in Fig. 1. For the OP and OS test data, 200,000 samples were randomly selected from approximately 800,000 initial data points. The arrival scores of ordinary earthquakes, OP and OS, contain about 20 times more data than those of LFEs, LP and LS, resulting in a significant data imbalance. To mitigate this effect, we assigned a weight 10 times larger to the loss function for LP and LS label data than for the OP and OS label data during training.

The model was trained for 150 epochs using a single Nvidia Quadro RTX6000 unit. Each epoch required approximately 45 minutes of computation time. The validation loss closely followed the training loss (Fig. 1), indicating no significant overfitting. For the subsequent analyses, we used the model from epoch 143, at which the validation loss reached its minimum value of 0.0215; this model is hereafter referred to as the FC (five-class) model.

During training, S-net waveforms, for which the vertical orientation of the seismometers is not guaranteed, were rotated into east–west, north–south, and vertical components based on sensor orientations reported by Takagi et al. (2019). No correction was applied to data from other stations. Although some datasets may include cases in which the orientations of the horizontal components are uncertain, this is not expected to significantly affect the performance of the trained model (Naoi et al., 2024).

2.2. Picking Performance

In this study, we use the sums of the P-phase scores (OP + LP) and S-phase scores (OS + LS) as the P- and S-phase arrival-time scores, respectively, for hypocenter determination. Event classification is then performed using the individual class scores. This approach enables stable hypocenter determination even for waveforms that are difficult to classify, compared with treating ordinary earthquakes and LFEs separately. For the probability traces obtained for each class, a peak detection algorithm (Virtanen et al., 2020) was applied to extract local maxima exceeding a predefined threshold. At this stage, peaks for which the score of the target phase is smaller than that of the other phase at the same time were discarded; for example, in the case of P-phase detection, peaks with P score lower than the S score were rejected. Peaks were also discarded if a higher score of the target phase exists within ± 1 s. For each extracted arrival-time, the class with the maximum score among the five class scores, excluding the noise class, was defined as the predicted class.

Using the picks and their predicted classes obtained from the test data, precision–recall curves were constructed. A true positive was defined as a pick with the correct predicted class occurring within ± 0.5 s of the labeled pick. A false positive was defined as a pick with no corresponding label within ± 0.5 s, whereas a false negative was defined as a labeled pick with no corresponding model pick within ± 0.5 s.

The results are shown in Fig. 2. For all phases for all non-noise phase classes, high precision values of 0.9 or higher were achieved even when low P- and S-wave picking thresholds of 0.05 were adopted. Therefore, P- and S-wave picking thresholds of 0.05 were used in the following analyses for the model evaluation. A schematic diagram of the evaluation method and its explanation are also provided in Fig. S1 and Text S1 of

Supplementary File 1 for reference.

The table in Fig. 2 summarizes the evaluation metrics for the test data. To account for class imbalance, the metrics are obtained by the confusion matrix normalized by the total number of true samples in each class. Precision exceeds 0.95 for all classes except the noise class; however, recall is somewhat lower for LP and LS.

Fig. 3 shows examples of inference results for LFE waveforms in the test data. Fig. 3a presents a waveform of a deep LFE with a hypocenter in the southwestern Niigata Prefecture, for which picks are listed in the JMA catalog. The results of applying the model developed in this study are also shown. The probability scores for LP and LS increase to nearly 1.0 around the labeled arrival times. Fig. 3b shows an example of a waveform associated with a deep low-frequency tremor originating in southern Nagano Prefecture, for which only the S-wave pick is listed in the JMA catalog. When the developed model is applied to this waveform, picks are obtained near the labeled arrival time, as well as additional picks around 18 s and 27 s. A close examination of the waveform shows that, although somewhat unclear, S-phase-like onsets can be observed in the horizontal components at these times. These results indicate that the model developed in this study can capture S phases even for low-frequency events lacking clear P phases, such as deep low-frequency tremors along the Nankai Trough.

The distribution of the differences between the detected picks and the ground-truth labels for the test data is shown in the lower panel of Fig. 4. For OP and OS, the mean differences are 0.0041 s and 0.0068 s, respectively, with standard deviations of 0.0707 s and 0.1145 s. For LP and LS, the mean differences are 0.0056 s and 0.020 s, with standard deviations of 0.1427 s and 0.1888 s, respectively. These results indicate slightly larger variability for LFEs compared to ordinary earthquakes.

2.3. Misclassification between Ordinary Earthquakes and LFEs

LFEs are richer in low-frequency components than ordinary earthquakes. In this study, however, waveforms are normalized using z-score normalization before being input into the model, thereby removing absolute amplitude information. As a result, the model may not fully exploit amplitude-related features, which could lead to misclassification between ordinary earthquakes and LFEs in some cases. To evaluate the misclassification rate between ordinary earthquakes and LFEs, we examined its dependence on hypocentral distance, magnitude, and focal depth (Fig. 5). Although no strong overall dependence on these factors is observed, the misclassification rate is generally less than 5% for ordinary earthquakes and less than 10% for LFEs. However, higher misclassification rates are observed in some local ranges. For hypocentral distance (Fig. 5, left column), the rate of misclassifying OS as LS exceeds 10% beyond 150 km, and the rate of misclassifying LP as OP also exceeds 10% beyond 60 km. In distance ranges where data are abundant, as well as in most other ranges, the misclassification rate is generally suppressed to less than 5%. Regarding magnitude dependence (Fig. 5, middle column), there is no clear tendency for large ordinary earthquakes to be misclassified as LFEs. However, approximately 10% of LFEs with magnitudes greater than 1.5 are misclassified as ordinary earthquakes. For focal depth (Fig. 5, right column), the rate of misclassifying OS as LS increases to more than 10% at depths of around 200 km.

3. Introduction of an LFE-Likeness Index

Using the FC model trained in Section 2 as a picker for continuous waveforms, we propose the following three-step procedure (1) to (3) to objectively evaluate whether each

detected event corresponds to an LFE or an ordinary earthquake. A flowchart of this procedure is also shown in Fig. S2.

- Process 1: Phase picking from continuous waveforms using the FC model.
- Process 2: Phase association and automatic hypocenter determination.
- Process 3: Event classification as an LFE or an ordinary earthquake based on the LP and LS scores at stations near the hypocenter.

It is important to note that phase classification and event classification are treated as two distinct steps in this framework. The FC model performs classification at the phase level (OP, OS, LP, LS), whereas the final classification of LFEs is conducted at the event level.

In Process 1, inference is first performed on three-component waveforms at each station using segments of 6000 samples, corresponding to 60 s. To avoid missing seismic phase arrivals near the edges of each time window, a 10-s overlap is applied, resulting in a 50-s step between consecutive windows. As in the accuracy evaluation of the model using test data described in the previous section, a predicted arrival time is defined as a local maximum in the P- or S-phase probability trace that exceeds a predefined threshold, is larger than the score of the other phase at the same time, and has no higher prediction score within ± 100 samples (± 1 s) of the peak. The OP, OS, LP, and LS probability values at each predicted arrival time are also retained.

In Process 2, phase association is performed using the PF method (Tamaribuchi et al., 2016), and hypocenter determination is carried out using the program employed in the routine processing of the JMA, together with a one-dimensional velocity structure (Hamada et al., 1983; Ueno et al., 2002). The PF method estimates plausible hypocenters by repeatedly distributing virtual sources around stations that detect seismic waves, enabling high-accuracy hypocenter determination even during periods of intense seismic

activity. To ensure the reliability of the determined hypocenters, we adopted only events for which P-wave picks were available at four or more stations, both P and S waves were used at two or more common stations, the latitude and longitude errors were less than 1 arcmin, and the depth error was less than 5 km. In the JMA routine processing program, magnitudes are calculated using vertical-component amplitudes of raw waveforms at stations where the signal-to-noise ratio exceeds 5. In this study, however, to estimate magnitudes for smaller events, amplitudes were measured using waveforms to which a 2-Hz high-pass filter had been applied. To account for systematic differences from M_{JMA} caused by this procedure, we derived a linear regression equation for events matched with the JMA catalog, using the magnitude obtained by the above procedure as the explanatory variable and M_{JMA} as the response variable, and applied the resulting correction. In addition, visual inspection of event waveforms for the seismic activity around Yamaguchi Prefecture described in Section 4 revealed that many events with uncorrected magnitudes less than -0.5 corresponded to background noise-level amplitudes. These events were therefore treated as having no reliable magnitude estimate.

For the automatic hypocenter determination procedure in Process 2, we first optimized the picking thresholds used in Process 1 to identify valid P- and S-wave picks. To this end, we applied the FC model to continuous waveform data recorded at 21 stations located around the source region of the 2000 Western Tottori earthquake (M_{JMA} 7.3; 34.8° – 35.8° N, 132.8° – 133.8° E). We generated multiple automatic earthquake catalogs by varying the P- and S-wave picking thresholds from 0.05 to 0.40 in increments of 0.05 and compared the resulting catalogs with the 100 hypocenters listed in the JMA catalog (Fig. S3a). All 64 combinations of P- and S-wave thresholds were evaluated by comparing the automatically determined hypocenters with those in the JMA catalog. The optimal

threshold combination was defined as that which maximized the number of matched events while minimizing the number of excess detections (Fig. 6a). Here, an automatically determined event was considered to match a JMA hypocenter when the differences in latitude and longitude were both less than 0.05° , the focal depth difference was less than 5 km, and the origin-time difference was less than 1 s. This analysis identified threshold values of 0.25 for P-wave picks and 0.10 for S-wave picks as the optimal combination. We adopted these thresholds in the analyses presented in Section 4 and later, which focus on the northern Yamaguchi region, another inland area of the Chugoku district. For reference, details regarding the results of applying these picking thresholds to the source region of the 2000 Western Tottori earthquake are provided in Text S2.

In Process 3, we define an index termed LFE-likeness, hereafter referred to as LIKE, from the LP and LS scores and use it to evaluate whether each detected event corresponds to an LFE. To improve robustness, we first compute the median LP and LS scores across the stations used for hypocenter determination and define them as *PLIKE* and *SLIKE*, respectively. We then compare the numbers of stations contributing to *PLIKE* and *SLIKE* and adopt the score derived from the larger number of stations as *LIKE*. If both scores are based on the same number of stations, we assign the larger of *PLIKE* and *SLIKE* to *LIKE*. Therefore, *LIKE* should be interpreted as an event-level index derived from multiple phase-level predictions, rather than as a direct output of the waveform classification model. We define *LIKE* as

$$PLIKE = \text{median}(Xp), \quad (1)$$

$$SLIKE = \text{median}(Xs), \quad (2)$$

$$LIKE = PLIKE \cdot I(n(Xp) > n(Xs)) + SLIKE \cdot I(n(Xp) < n(Xs))$$

$$+ \max(PLIKE, SLIKE) \cdot I(n(Xp) = n(Xs)) \quad (3)$$

where (Xp) and (Xs) denote the sets of LP and LS scores obtained at the selected stations for a given event, ($n(X)$) represents the number of available scores in set (X), and (I) is the indicator function.

To evaluate the definition of LIKE, we applied the FC model to continuous waveform data around the arrival times of events listed in the JMA catalog (Fig. S5) using the P- and S-wave picking thresholds of 0.05 for analyses for the model evaluation. The analysis used data from the Chugoku–Shikoku district and other regions of Japan where LFEs were reported between 1 February 2024 and 31 January 2025 (Fig. S4). We compared median-based and mean-based definitions of PLIKE and SLIKE and found that the median-based approach provides better discrimination between LFEs and ordinary earthquakes (Fig. S6). We also examined the effect of the number of contributing stations. The classification performance of both PLIKE and SLIKE improved and became more stable as the number of effective stations increased (Fig. S7); details are provided in TextS3.

To classify events as LFEs, we adopted a threshold of $LIKE \geq 0.05$, which correctly identifies more than 99% of LFEs in the JMA hypocenter catalog. Fig. 7 shows the relative frequency distributions of LIKE values for LFEs and ordinary earthquakes. The analysis used all seismic events in the Chugoku–Shikoku district, including tectonic tremor, recorded between 1 February 2024 and 31 January 2025. In addition, we incorporated LFE data from other regions of Japan where LFEs have been reported, excluding tectonic tremor events (Fig. S4). At a threshold of $LIKE = 0.05$, the recall for LFEs reaches 0.993, whereas recall decreases rapidly as the threshold increases further

(orange line in Fig. 7). At the same threshold, 99.9% of ordinary earthquakes in the JMA catalog are correctly classified as non-LFEs. Consistent with this result, the relative frequency of LFEs (orange bars in Fig. 7) decreases markedly below $\text{LIKE} = 0.05$. In contrast, more than 99% of ordinary earthquakes (light-blue bars in Fig. 7) have LIKE values below 0.001. Although both LFEs and ordinary earthquakes occur in the range $0.001 \leq \text{LIKE} < 0.05$, their frequencies are low.

For reference, Fig. S8 shows the distribution of LIKE values obtained using the optimized P- and S-wave picking thresholds of 0.25 and 0.10, respectively. Under these stricter picking conditions, the highest LIKE threshold that still maintains an LFE recall of 99% or higher is 0.10, likely reflecting the higher S-wave picking threshold. Nevertheless, the LIKE threshold of 0.05 adopted above also provides excellent classification performance under these conditions, with a recall of 0.995 and a precision of 0.999 for LFEs. Therefore, we use $\text{LIKE} \geq 0.05$ as the common classification threshold in the following analyses.

4. Application of LIKE to Continuous Waveform Data Around Yamaguchi Prefecture

A seismic swarm has been active in northern Yamaguchi Prefecture since 1 February 2025 at depths greater than 20 km. According to the JMA catalog, this activity was accompanied by LFEs from February to early March (Fig. S9; details are provided in TextS4) and the results of a stationary ETAS analysis suggest that processes other than conventional earthquake triggering may contribute to the overall earthquake occurrence rate (Fig. S11 and TextS6).

We applied the procedures described in Section 3 to continuous waveform data

recorded between 1 February and 30 April 2025 at 32 velocity stations located in and around Yamaguchi Prefecture (33.7° – 35.0° N, 130.8° – 132.4° E). We then compared the automatically determined hypocenters with those listed in the JMA catalog.

The proposed method determined 6,614 hypocenters during the study period, approximately 2.4 times the number reported in the JMA catalog (Fig. 8a). Using the same matching criteria as in Section 3—differences of less than 0.05° in latitude and longitude, less than 5 km in depth, and less than 1 s in origin time—we matched 2,431 events to hypocenters in the JMA catalog. These matched events comprise 2,411 ordinary earthquakes and 20 LFEs. The method successfully detected all but one of the LFEs listed in the JMA catalog. Among the automatically determined hypocenters, 305 events have $\text{LIKE} \geq 0.05$. Of these, 146 are located outside the main swarm area (black rectangle in Fig. 8a). Most of these events cluster near 34.2° N, 131.2° E, within the region enclosed by the dashed black line in Fig. 8a, and near 33.8° N, 130.9° E, at depths of 0–20 km. Inspection of their waveforms together with aerial imagery of the source areas suggests that these events are quarry blasts rather than natural earthquakes.

Within the swarm region, high-LIKE events delineate a broad zone of seismicity at depths greater than 20 km. Fig. 8b shows an enlarged view of the hypocenter distribution in the swarm area. To better resolve the spatial distribution of seismicity, we relocated the hypocenters using TomoDD-SE (Zhang and Thurber, 2003, 2006). The proposed method detected 5,687 events within the swarm region, more than 2.3 times the number reported in the JMA catalog. The magnitude of completeness (M_c ; Wiemer and Wyss, 2000) is 0.0, substantially lower than that of the JMA catalog ($M_c = 0.5$). This result indicates that the present catalog captures a significantly large number of small-magnitude events.

The spatial and temporal distributions of LFE-classified events, defined here as events

with $\text{LIKE} \geq 0.05$, and those non-LFE-classified events largely overlap (Fig. 9). Nevertheless, LFE-classified events tend to concentrate at greater depths and in the western part of the swarm region. Fig. 9a shows the distribution of LFE-classified events within the swarm region. At the onset of the activity, ten events occurred over a two-day period near the western edge of the swarm region at depths of approximately 40 km. Subsequently, intermittent activity continued until day 20 at depths greater than 34 km and west of 131.54°E , within the area enclosed by the dashed black boundary in Fig. 9a. After day 26, seismicity became active immediately east of this initial cluster at shallower depths and gradually expanded from west to east and from deeper to shallower levels. Non-LFE-classified seismicity exhibited a similar temporal evolution (Fig. 9b). However, its distribution extended beyond that of the LFE-classified events, reaching shallower depths and spreading farther to the east and north.

Figure 9c illustrates the temporal variation of LIKE values. Excluding events shallower than 20 km, which correspond to the events with $\text{LIKE} < 10^{-4}$ before day 20 in Fig. 9c, only LFE-classified events occurred during the first 20 days, when the deep cluster was active. After day 20, LIKE values spanned nearly the full range from 0 to 1, indicating the coexistence of events with a wide spectrum of LFE-like characteristics. Among the 20 events matched to LFEs in the JMA catalog, LIKE values range from 0.002 to 0.818. Thirteen of these events satisfy the criterion for LFE classification, whereas seven were classified as non-LFE events. In total, 159 LFE-classified events were detected within the swarm region, approximately 7.6 times the number of LFEs listed in the JMA catalog.

The threshold $\text{LIKE} \geq 0.05$ should be interpreted as an empirical criterion that works well for the calibration dataset, but may require adjustment depending on the regional

characteristics of seismicity. The frequency distribution of LIKE values for the swarm activity is shown in Fig. 9d. Unlike seismicity in other regions corresponding to the calibration dataset, where events with $0.001 \leq \text{LIKE} < 0.05$ are rarely observed, the swarm activity exhibits a continuous distribution across this range of LIKE values. This result suggests that the LIKE threshold derived from the calibration dataset may not always provide a sharp separation between LFEs and ordinary earthquakes in all seismic regions.

5. Discussion

5.1. Relationship between LIKE and Frequency-Domain Characteristics

In contrast to seismicity in other regions, the northern Yamaguchi swarm exhibits a continuous distribution of LIKE values across the LFE classification threshold of $\text{LIKE} = 0.05$, making it difficult to distinguish LFEs from ordinary earthquakes using this criterion alone. To investigate the origin of this characteristic, we applied the frequency-domain method proposed by Nakajima and Hasegawa (2021; hereafter NH) to the automatically determined hypocenters obtained in this study. The NH method distinguishes LFEs from ordinary earthquakes based on spectral characteristics; details of method and examples of analyzed waveforms are provided in TextS5 and Fig. S10.

Most events in the swarm region do not satisfy the LFE criteria defined by NH. Fig. 10a shows the distributions of FI and f_p values calculated following the procedure of NH. Among the LFE-classified events, only five satisfy the NH criteria for LFEs, defined as $\text{FI} \leq -0.75$ and $f_p \leq 4$ Hz, whereas the remaining events fall outside the NH-defined LFE domain.

Notably, many LFEs listed in the JMA catalog also fall outside the NH-defined LFE domain. Even among the LFEs listed in the JMA catalog, indicated by red-outlined circles

in Fig. 10a, many cluster near $f_p \approx 10$ Hz, corresponding to the upper-frequency limit of the LFE population identified by NH, or exhibit FI values greater than 0. Comparison of the relative frequency distributions of FI and f_p further highlights the differences between the swarm activity and the NH reference population. Non-LFE-classified events show a primary distribution that is similar to, or slightly shifted toward higher frequencies than, that of ordinary earthquakes reported by NH, shown by black curves in the relative-frequency plots of Fig. 10a. In contrast, although the f_p distribution of LFE-classified events largely overlaps that of ordinary earthquakes in NH, their FI distribution extends toward lower values, with a secondary concentration around $FI \approx -0.3$.

For comparison, Fig. 10b shows the FI- f_p distribution for seismicity in western Tottori Prefecture (Fig. 6b), which was used in Section 3 to optimize the P- and S-wave picking thresholds. All events satisfying the NH-defined LFE criteria correspond either to LFEs listed in the JMA catalog or to events independently identified as LFEs through visual waveform inspection. Although some LFEs listed in the JMA catalog fall outside the NH-defined LFE domain, LIKE successfully classifies these events as LFEs.

A major practical limitation of LIKE is its sensitivity to non-natural seismic sources, such as quarry blasts. As shown in Fig. 8a, a substantial number of events with high LIKE values ($LIKE \geq 0.05$) are located outside the swarm region and were identified as quarry blasts. This indicates that high LIKE values do not necessarily imply natural LFEs. Fig. 10c shows the corresponding FI- f_p distribution for events located outside the swarm region in northern Yamaguchi Prefecture (Fig. 8a). Events corresponding to quarry blasts tend to exhibit lower-frequency characteristics than events interpreted as natural earthquakes. This tendency is consistent with the high LIKE values frequently assigned to quarry blasts.

Previous spectral-analysis studies have shown that seismic signals generated by mining-related blasts commonly exhibit dominant frequencies comparable to, or lower than, those of natural earthquakes, together with relatively long signal durations (Biessikirski and Jakóbczyk, 2025). These characteristics may reflect stronger attenuation of high-frequency energy in the shallow crust, a greater contribution from surface waves, and longer source-time functions associated with source processes that differ from those of natural earthquakes (McLaughlin et al., 2004; Kan et al., 2022; Yoshida et al., 2024).

In summary, LIKE is influenced, at least in part, by the FI and f_p values of individual events. Seismicity in the northern Yamaguchi swarm region is characterized predominantly by frequency-domain properties similar to those of ordinary earthquakes. However, many events occupy the boundary region of the NH-defined LFE domain in FI- f_p space, which likely contributes to the continuous distribution of LIKE values and the lack of a clear separation between LFE- and non-LFE-classified events.

Although LIKE is associated with FI and f_p , these two frequency-domain indices alone cannot fully explain the observed variation in LIKE values. Events with similar FI and f_p values can exhibit substantially different LIKE values, suggesting that LIKE captures additional waveform characteristics beyond those represented by FI and f_p . Possible candidates include source- or path-related features reported for LFEs, such as resonance associated with cracks, fluids, or gas near the source region, as well as prolonged signal durations resulting from long rupture processes (Hensch et al., 2019; Haruyama et al., 2020; Ikegaya and Yamamoto, 2020). Whether LIKE is sensitive to such characteristics remains an open question and warrants further investigation.

5.2. Spatiotemporal Distribution of LIKE-Classified Events in the Yamaguchi

Swarm and Its Relation to Fluid Process

Fig. 11a shows the temporal evolution of hypocentral distance from the initial swarm activity. We define the source location of the initial activity as the median latitude, longitude, and depth of the ten events that occurred between 1 and 3 February 2025. To emphasize short-range migration, only events located within 20 km of this reference point are shown. The figure also includes theoretical diffusion fronts calculated for fluid-pressure diffusion originating from the initial hypocentral cluster (Shapiro et al., 1997).

Previous studies based on observations of natural seismicity migration, fluid-injection experiments, and laboratory measurements have suggested usual crustal hydraulic diffusivities of approximately $0.01\text{--}10\text{ m}^2/\text{s}$ (e.g., Scholz, 2002; Talwani et al., 2007; Ingebritsen and Manning, 2010), although significantly larger values, in the range of $20\text{--}100\text{ m}^2/\text{s}$, are also reported in the literature (Antonioli et al., 2005; Shimojo et al., 2021). Okada et al. (2015) and Amezawa et al. (2021) among others have reported values of $0.01\text{--}5\text{ m}^2/\text{s}$ for earthquake swarms in Japan. During the first 25 days following the onset of activity, the number of events was limited, and no clear migration trend was apparent. Nevertheless, most hypocenters remained within the diffusion front corresponding to $D = 2.5\text{ m}^2/\text{s}$. In contrast, after seismicity reactivated on day 26, hypocenters expanded well beyond this diffusion front.

To examine this later stage in greater detail, Fig. 11b shows hypocentral distance as a function of time relative to the median location of the six events that occurred on day 26, corresponding to 26 February 2025. The overall migration pattern broadly follows diffusion fronts with $D = 2.5\text{--}5.0\text{ m}^2/\text{s}$, although the migration rate varies with time and occasionally reverses along the primary migration direction. During the first ~ 10 days after reactivation, the migration is consistent with $D \approx 2.5\text{ m}^2/\text{s}$. Subsequently, the

524 migration accelerates and reaches distances corresponding to $D \approx 5.0 \text{ m}^2/\text{s}$ by ~ 25 days
525 after reactivation. Hypocenters then retreat to within the $D \approx 2.5 \text{ m}^2/\text{s}$ diffusion front and
526 continue to migrate along this front until approximately 50 days after reactivation. For
527 reference, these trends are also observed when the data are plotted separately for LFE-
528 classified and non-LFE-classified events (Fig. S12).

529 A diffusivity equal to or greater than $2.5 \text{ m}^2/\text{s}$ implies relatively rapid migration
530 compared with most fluid-driven swarm activity reported in Japan. Because the swarm
531 occurs predominantly at depths greater than 20 km, where crustal porosity is generally
532 much lower than in the typical seismogenic crust (Chen et al., 2020), the inferred
533 diffusivity is consistent with relatively high permeability, low fluid viscosity, or a
534 combination of both.

535 The complex temporal changes in migration rate and the sustained upward migration
536 of seismicity from deep to shallow levels observed in Fig. 11 suggest that the swarm
537 activity cannot be explained solely by simple pressure diffusion. Additional processes
538 involving fluid transport and/or fluid generation may also contribute to the observed
539 migration pattern. A recent study by Nakajima et al. (2026), which analyzed hypocenter
540 migration and the thermal structure of the crust and upper mantle beneath the swarm
541 region, proposed that fluids generated by dehydration reactions of hydrous minerals may
542 play an important role in the swarm activity. In their model, high-temperature fluids
543 ascending from the upper mantle may be supplied to permeable fault zones in the lower
544 crust, where they could promote additional dehydration reactions, elevate pore-fluid
545 pressure, and facilitate brittle failure. The resulting interaction among fluid supply, fluid
546 generation, and heat transport may provide a mechanism for sustaining long-term
547 hypocenter migration. Although the observations presented here do not directly test this

model, the complex migration pattern shown in Fig. 11 is broadly consistent with the involvement of processes beyond simple pressure diffusion.

The seismic velocity structure estimated by double-difference tomography also provides additional evidence consistent with fluid involvement in the swarm region (Fig. 12). Based on linear interpolation of V_p/V_s values obtained on a grid with horizontal and vertical spacings of approximately 5 km, cross-sections along the principal trend of the LFE-classified events reveal elevated V_p/V_s regions. These regions are observed not only beneath the southeastern part of the swarm region, at approximately 15 km distance and 25 km depth in Fig. 12b, but also beneath the deeper western part of the swarm and its downward extension, at approximately 5–10 km distance and 30–40 km depth in Fig. 12b. Similar high- V_p/V_s regions are observed in cross-sections along latitudes 34.45°N and 34.50°N , where tomography grid nodes are available (Fig. S13).

Elevated V_p/V_s ratios are commonly interpreted as indicators of fluids and/or partial melt. In addition, crustal LFEs are known to occur primarily from the lower crust to the uppermost mantle and are generally considered to be associated with elevated pore-fluid pressure under high-temperature conditions (e.g., Hasegawa and Nakajima, 2022). The concentration of LFE-classified events in the deeper and western parts of the swarm region spatially coincides with the high- V_p/V_s regions identified in this study. This spatial association is consistent with a link between LFE-classified events and fluid-rich zones. However, the present observations do not uniquely constrain the origin, transport pathways, or physical properties of the fluids potentially involved in the swarm activity.

6. Conclusion

We developed a five-class machine-learning model based on PhaseNet that explicitly

incorporates LFE classification. The trained model accurately classifies the P- and S-wave phases of ordinary earthquakes and LFEs, as well as noise, while providing corresponding arrival-time picks.

Applying the model to continuous waveform data, followed by phase association and hypocenter determination, yielded more than twice as many events as existing catalogs. In addition, LIKE, derived from LP and LS scores, provides an event-level index for distinguishing LFEs from ordinary earthquakes. However, an important limitation is that high LIKE values are not unique to natural LFEs. In particular, many quarry blasts also exhibit high LIKE values, indicating that the LIKE index alone is insufficient to distinguish LFEs from anthropogenic seismic sources. Addressing this limitation will be essential for practical applications.

The northern Yamaguchi swarm exhibits a markedly different LIKE distribution from seismicity in other parts of the Chugoku and Shikoku regions, with a continuous distribution across the LFE classification threshold rather than a clear separation between LFE and ordinary-earthquake populations. Analyses of hypocenter migration and seismic velocity structure are consistent with fluid involvement in the swarm activity and show that LFE-classified events are concentrated in the deeper western part of the swarm region.

List of abbreviations

JMA	Japan Meteorological Agency
LFE	Low-Frequency Earthquake
PF	Phase combination Forward search
NH	Nakajima and Hasegawa, 2021

FI Frequency-Index

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

The FC model trained using the JMA unified catalog data is available at <https://github.com/kngshimojo/Five-Class-model-picker>. Seismic waveform data related to the routine seismic observations in Japan (including networks other than Hi-net) are available at <http://www.hinet.bosai.go.jp/?LANG=en>. The JMA unified catalog is available at <https://www.data.jma.go.jp/svd/eqev/data/bulletin/index.html>.

Competing interests

The authors declare no competing interests.

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Authors' contributions

KS was the primary contributor to analysis and manuscript writing. MN, SH and BE contributed to the examination and interpretation of the

results. All authors contributed to the writing and have read and approved the final manuscript.

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Figure captions

Fig. 1. Learning curve and dataset composition for the FC model. Learning curves of the FC model during training using the dataset compiled by Naoi et al. (2024). Blue and orange lines show the loss functions for the training and validation datasets, respectively. The minimum validation loss occurred at epoch 143, indicated by the orange circle. The table in the upper part of the figure shows the number of training, validation, and test samples for each label.

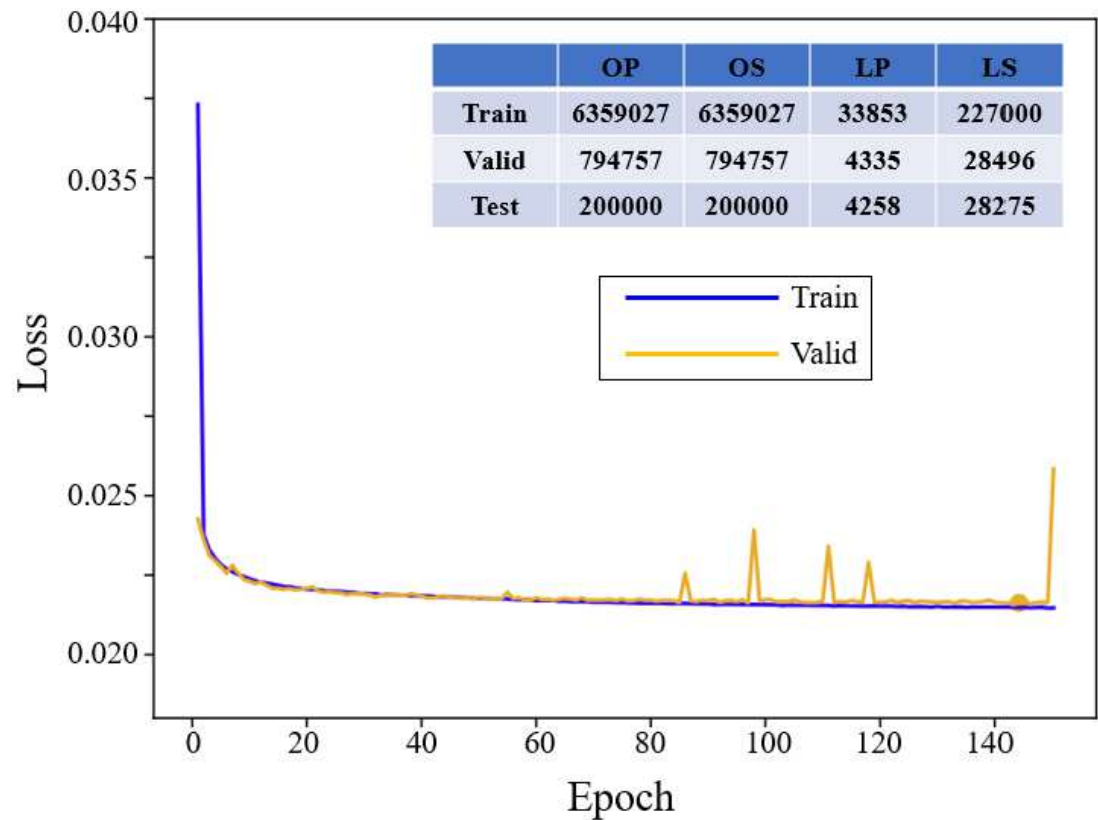


Fig. 2. Precision-recall curves and evaluation metrics for the FC model. Precision-recall curves for the test data at P- and S-wave picking thresholds of 0.05. Circles, inverted triangles, triangles, and squares indicate class probability thresholds of 0.05, 0.10, 0.20, and 0.50, respectively. For each non-noise class, a sample was counted as a positive prediction when its probability exceeded the corresponding threshold and was the highest

among the non-noise classes. Precision and recall were then computed against the corresponding ground-truth class after normalizing the confusion matrix by the total number of true samples in each class. The inset table summarizes the evaluation metrics derived from a confusion matrix constructed by assigning each sample to the non-noise class with the highest predicted probability when the P- or S-wave picking probabilities exceeded 0.05, and to the noise class otherwise.

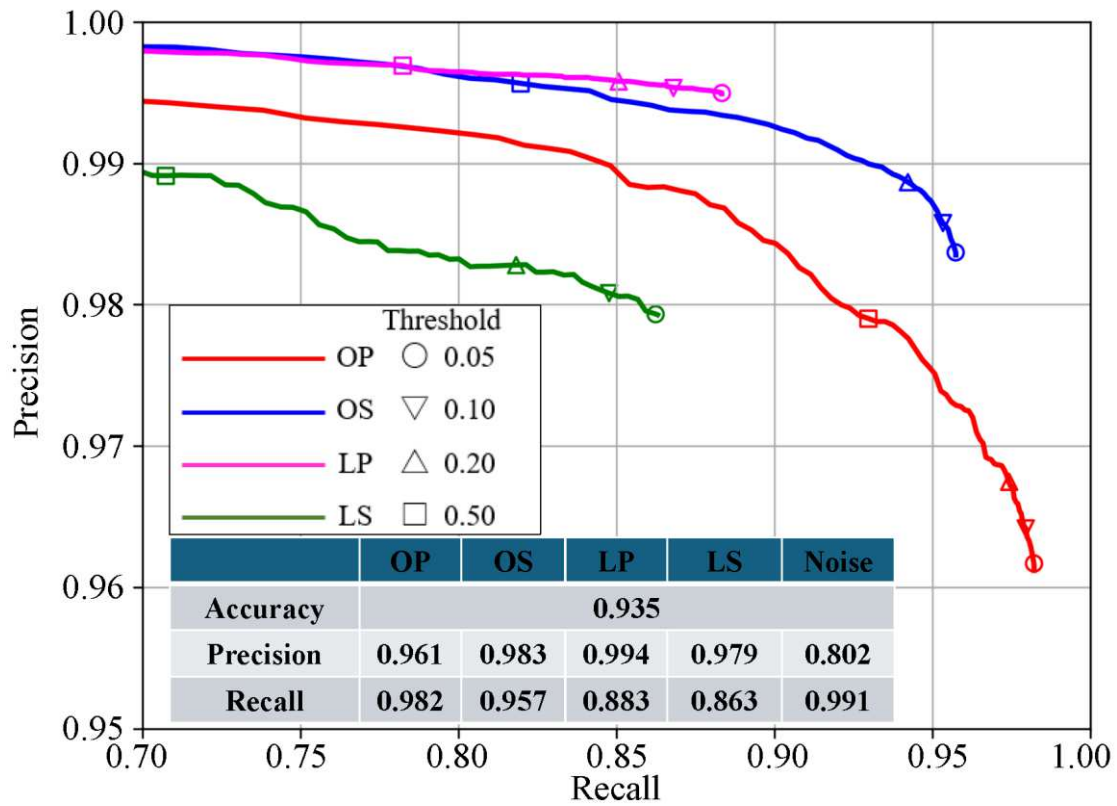


Fig. 3. Examples of LFE waveforms included in the test data. (a) Example of waveform data containing manually picked LP and LS labels. The purple and green dashed vertical lines in the waveform panels indicate the manual LP and LS picks, respectively. The waveform amplitudes of each component are standardized. The lower panel shows the five-class prediction results obtained using the FC model. The purple and green solid lines indicate the predicted LP and LS arrival times, respectively. Although the OP and OS probability traces are plotted in red and blue, respectively, they are nearly invisible

because their values remain close to zero throughout the time window; (b) Example of waveform data associated with deep low-frequency tremor, for which only an LS label is manually picked. The lower panel shows the corresponding prediction results obtained using the FC model.

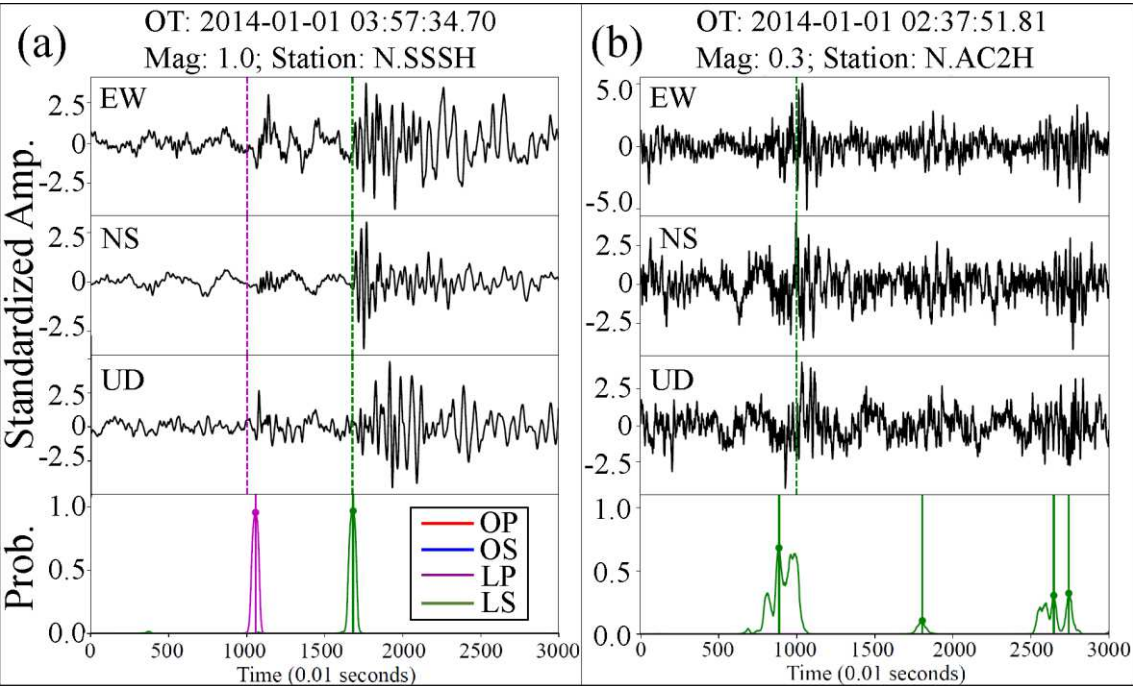


Fig. 4. Distributions of probability scores and arrival-time residuals. Frequency distributions of the probability scores for each label in the test data are shown in the top row. Frequency distributions of the arrival-time residuals, defined as the differences between predicted and labeled arrival times, are shown in the bottom row.

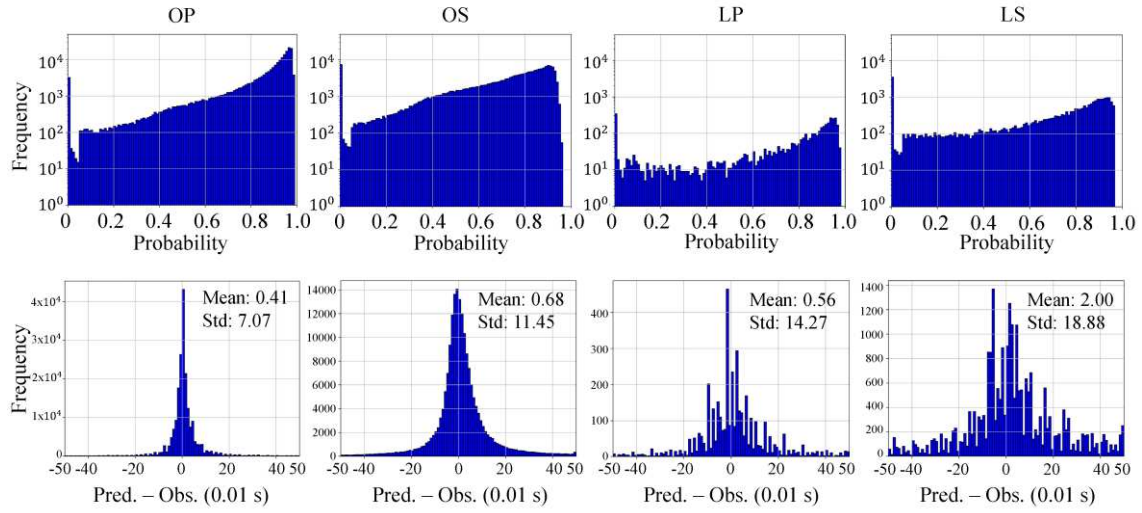


Fig. 5. Misclassification rates between ordinary-earthquake and LFE phase labels. Misclassification rates from ordinary-earthquake phase labels to LFE phase labels are shown in the top row, and those from LFE phase labels to ordinary-earthquake phase labels are shown in the bottom row. The data distributions are shown in the inset panels within each frame.

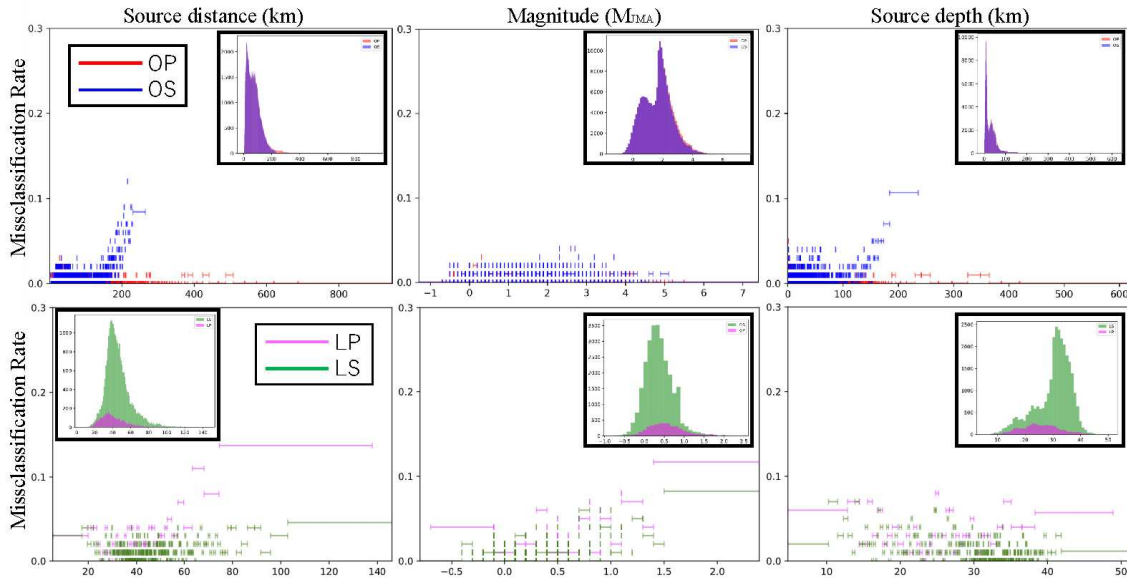


Fig. 6. Optimization of P- and S-wave picking thresholds for automatic hypocenter determination. (a) Heat map of evaluation results for different combinations of P- and S-

wave picking thresholds. Each cell corresponds to one threshold pair, and the color indicates the equal-weight scalarization score used for visualization. The definition of this score is shown at the bottom of the figure. M_{ij} denotes the number of events matched to the JMA catalog, whereas E_{ij} denotes the number of excess (unmatched) events for each combination of P- and S-wave thresholds indexed by i and j . To balance these two metrics, M_{ij} and E_{ij} are normalized to the range $[0, 1]$, and the score is defined so that larger M and smaller E yield higher values. The optimal threshold combination is selected by first maximizing M_{ij} and then minimizing E_{ij} . The cell outlined by a thick border indicates the threshold combination selected as optimal, and, in this case, it also corresponds to the maximum value of the scalarization score; (b) Distribution of automatically determined hypocenters using the optimal picking thresholds of 0.25 for P waves and 0.10 for S waves. Gray circles indicate determined events, red-outlined circles indicate events matched to JMA hypocenters, and green circles indicate events which are visually confirmed to be LFE.

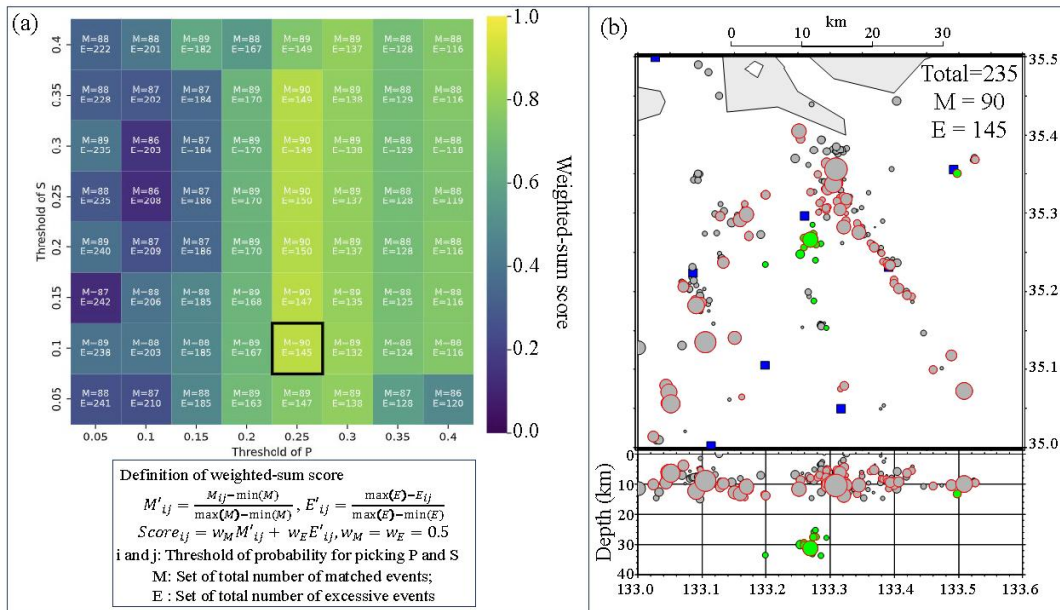


Fig. 7. Relative frequency distribution of LIKE values used to define the LFE

classification threshold. Relative frequency distribution of $\log_{10}(\text{LIKE})$ for all seismicity, including deep low-frequency tremors, in the Chugoku and Shikoku regions and LFEs, excluding tremor events, in other parts of Japan, as listed in the JMA catalog from 1 February 2024 to 31 January 2025. The $\log_{10}(\text{LIKE})$ values are divided into bins with increments of 0.1.

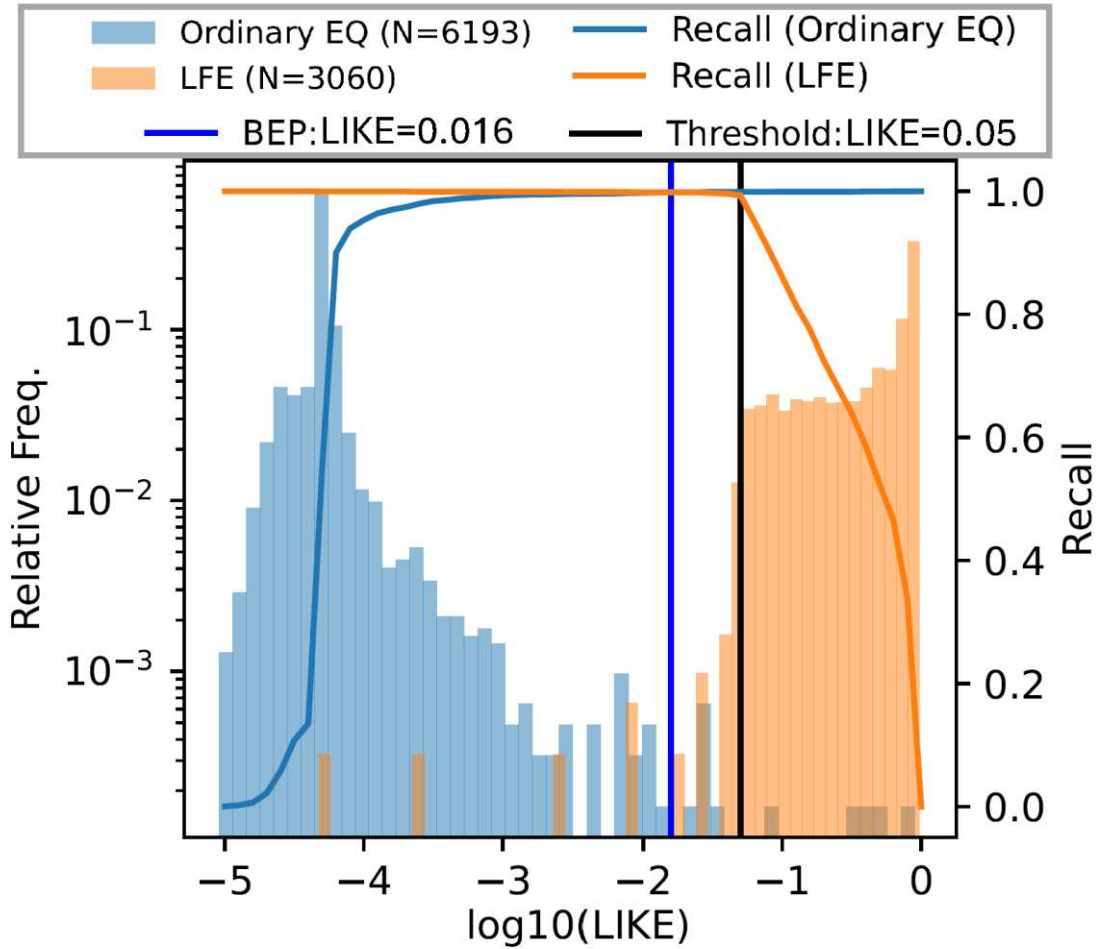


Fig. 8. Application of automatic hypocenter determination and LIKE calculation to the Yamaguchi Prefecture region. (a) Distribution and LIKE values of the hypocenters determined in this study. Circles and diamonds indicate determined events; diamonds indicate events without magnitude estimates. Circle size indicates magnitude. Red-outlined circles indicate events matched to LFEs listed in the JMA catalog. Blue squares

indicate the velocity stations used in this analysis. The black solid rectangle indicates the swarm area enlarged in (b), whereas the area enclosed by the black dashed line indicates a region where quarry blasts frequently occur. The colors of the circles and diamonds indicate LIKE values, following the color scale on the right. Events with $\text{LIKE} \geq 0.05$ are classified as LFEs in this study; (b) Distribution of hypocenters in the swarm area, corresponding to the black solid rectangle in (a). The hypocenters were relocated by the double-difference tomography method of Zhang and Thurber (2006).

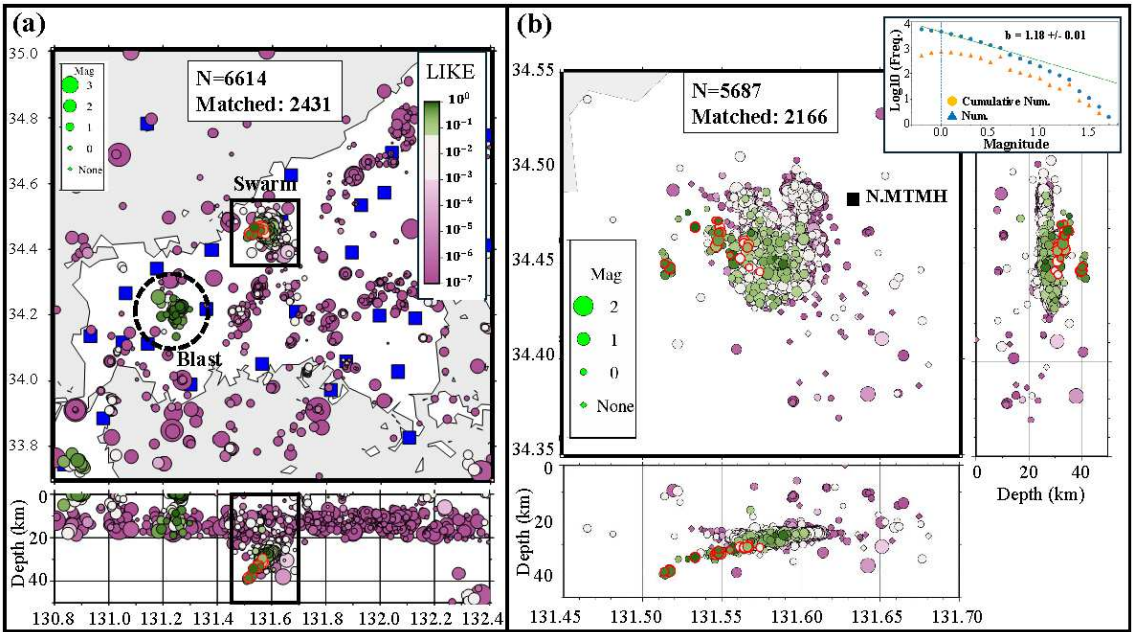


Fig. 9. Spatiotemporal distribution of hypocenters and LIKE values in the swarm area. (a) Distribution of hypocenters with $\text{LIKE} \geq 0.05$. Color of circles and diamonds indicate elapsed days, following the color scale at the bottom right of the figure. Black-outlined circles indicate events matched to LFEs listed in the JMA catalog. Gray circles indicate all hypocenters determined in this study; (b) Distribution of hypocenters with $\text{LIKE} < 0.05$; (c) Temporal variation of LIKE values. The colors of the circles and diamonds indicate LIKE values, following the color scale in Fig. 8a; (d) Relative frequency distribution of LIKE values. The cyan bars indicate the LIKE distribution for events in

the swarm area. The magenta and green stepped lines indicate the distributions for ordinary earthquakes in the Chugoku and Shikoku regions and for LFEs, respectively, corresponding to the cyan and magenta histograms in Fig. 7.

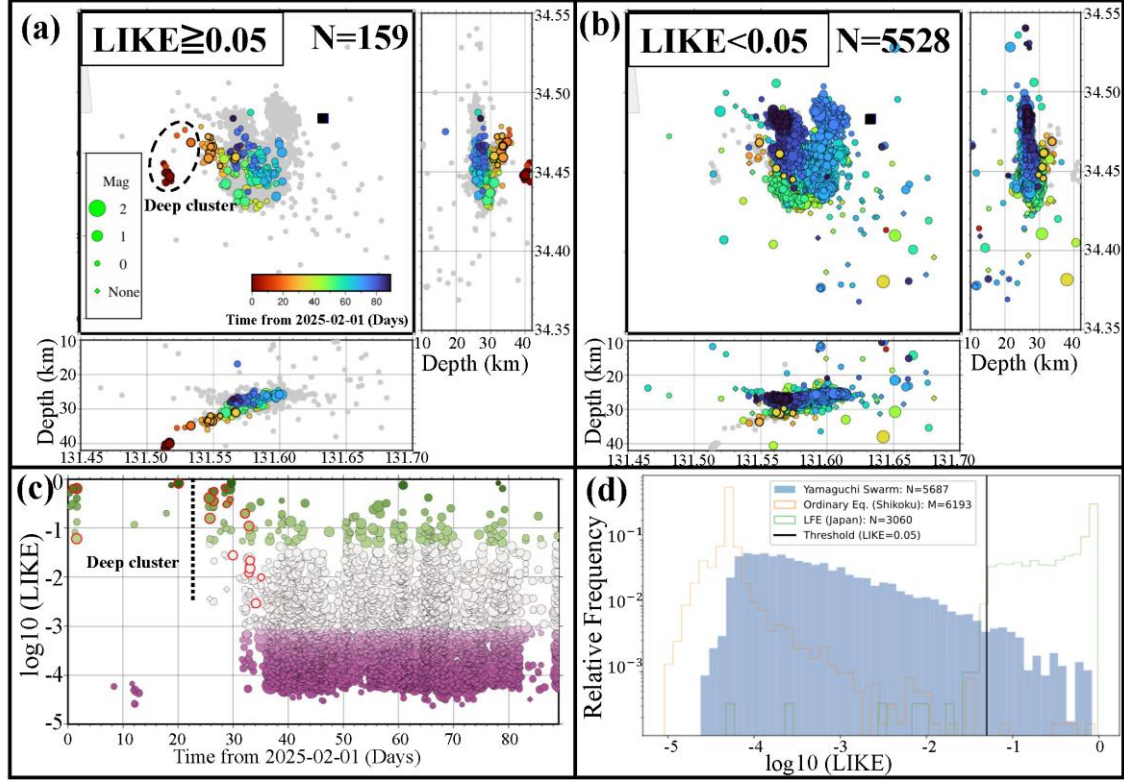


Fig. 10. Distribution of FI and f_p for events determined in this study. (a) The FI- f_p distribution for events in the swarm area. Circle colors indicate LIKE values, following the color scale in Fig. 8. Red-outlined circles indicate events matched to LFEs in the JMA catalog. The gray dotted region indicates the LFE criteria defined by Nakajima and Hasegawa (2021; NH). The upper inset shows the relative frequency distributions of FI for events with $\text{LIKE} \geq 0.05$ and $\text{LIKE} < 0.05$, using the same colors as in the legend. The right inset shows the corresponding relative frequency distributions of f_p . The black box and gray bars in the inset histograms indicate the relative frequency distributions of ordinary earthquakes and LFEs, respectively, reported by NH for events occurring within the continental crust of the Japanese archipelago from 2003 to 2017, at depths of 0 to 35

km) in Fig. 4 of Nakajima and Hasegawa, 2021; (b) Events in San-in region determined in Section 3 (Fig. 6b). Circles with orange outline indicate events which are visually confirmed to be LFE; (c) $FI-f_p$ distribution for events detected outside the swarm area in northern Yamaguchi Prefecture, including quarry blasts shown in Fig. 8a. Circles with blue outline are events in the blast area (34.13° – 34.26° N, 131.15° – 133.35° E, depths of < 10 km). Other events are located outside the blast area and at depths of 10 km or more.

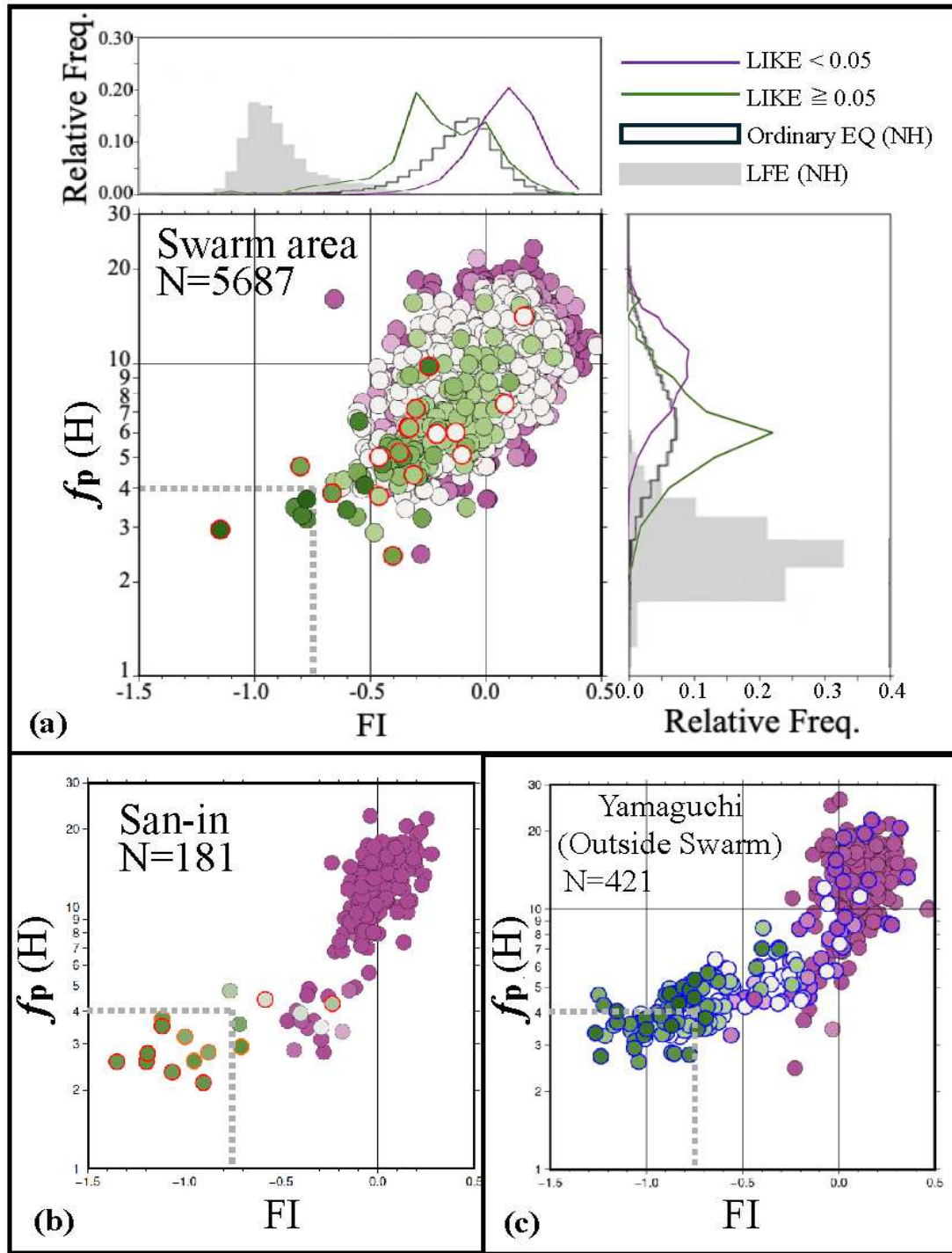


Fig. 11. Temporal evolution of hypocentral distance in the swarm area at depths of 20 km or greater. (a) Hypocentral distance from the initial swarm location as a function of elapsed time since the first event during the study period. The first event occurred at 04:44 on 1 February 2025. The initial swarm location is defined as the median latitude,

longitude, and depth of the ten events that occurred between 1 and 3 February. To focus on short-range migration near the initial activity, only events within 20 km of this reference location are shown. The red solid line indicates the theoretical diffusion front for $D = 2.5 \text{ m}^2/\text{s}$, assuming fluid-pressure diffusion from the location and time of the initial activity. Thin black lines indicate diffusion fronts for $D = 1.0, 5.0, 7.5$, and $10 \text{ m}^2/\text{s}$; (b) Same as (a), but for seismicity after the reactivation on 26 February. Time is measured from the first event on that day, and distance is measured from the median hypocenter of the six events that occurred on 26 February. The red solid line indicates the diffusion front for $D = 5.0 \text{ m}^2/\text{s}$, and thin black lines indicate diffusion fronts for $D = 2.5, 7.5$, and $10 \text{ m}^2/\text{s}$.

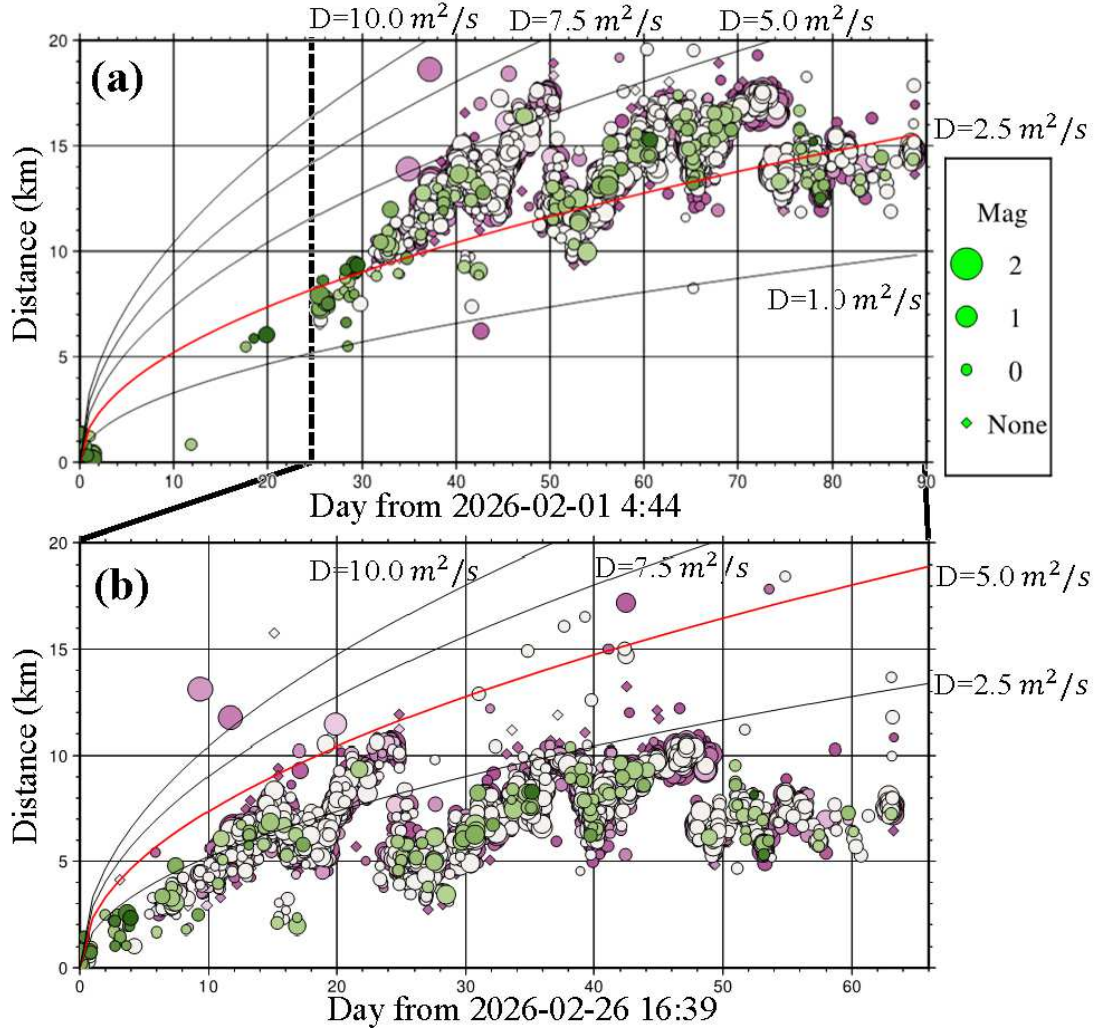
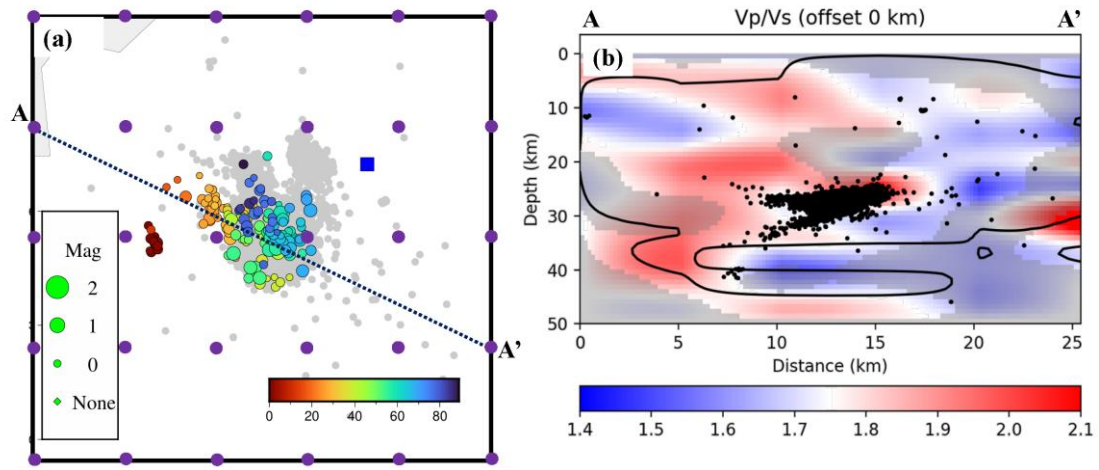


Fig. 12. Vp/Vs cross-section along the trend of the LFE-classified events. (a): Grid configuration of the analysis area used for the velocity structure inversion, overlain by the distribution of LFE-classified events, as in Fig. 9a. The grid spacing is 0.05° horizontally, corresponding to approximately 5 km, and 5 km, vertically; (b) Cross section of the Vp/Vs ratio along line A-A' in (a). The Vp/Vs value, DWS value, and recovery rates shown in this panel were obtained by linearly interpolating the values at each grid in (a). Black dots indicate all events determined within 5 km of the cross-section. Gray shading indicates the area where the recovery rate in the checkerboard resolution test is less than 0.2. Black contour indicates the line of DWS = 50 line, which approximately

930 marks the boundary between high- and low-resolution areas.



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